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RESEARCH ARTICLE

A Combined Image Deblurring Using Image Enhancements

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Abstract*— *While we capture images we used to get the noise to remove the noise we are using so many techniques which were not at reached the user requirement finally we came up through three paradigms which can fulfil user requirements: 1) the deterministic filter; 2) Bayesian estimation; and 3) the conjunctive deploring algorithm (CODA), which performs the deterministic filter and Bayesian estimation in a conjunctive manner. We point out the weaknesses of the deterministic filter and unify the limitation latent in two kinds of Bayesian estimators. We further explain why the CODA is able to handle quite large blurs beyond Bayesian estimation. Finally, we propose a novel method to overcome several unreported limitations of the CODA. Although extensive experiments demonstrate that our method outperforms state-of-the-art methods with a large margin, some common problems of image deblurring still remain unsolved and should attract further research efforts.

Keywords: - Bayesian estimation; blind image deconvolution; image sharpening; Alpha tonal correction; Blur Removing

I. INTRODUCTION

Photo such as astronomical imaging and consumer photography. Generally, there are many properties of a camera and a scene that can lead to blur, i.e., spatially uniform defocus blur dependent on depth, spatially varying defocus blur due to focal length variation over the image plane, spatially uniform blur due to camera translation, spatially varying blur due to camera roll, yaw and pitch motions, and spatially varying blur due to object movements. Numerous algorithms have proposed to address one or more of these individual blurs [1]–[12]. Although tremendous progress has been recently made, the results for quite large blurs (blur kernels of 100 100 pixels and larger) and severe noise are still far from perfect. In this paper, we do not restrict ourselves to a specific kind of blur but view this problem from a more generalized point of view in order to cover common principles in sharpening various blurs. Our goal is to reveal the limitations and potentials of recent methods when dealing with quite large blurs and severe noise. What are the main challenges and what are the key components that make handling quite large blurs and severe noise possible? What should attract further research ef- forts in the future? Additionally, we design a novel deblurring method to handle various large blurs and significant noise.

We consider that the research on this topic have evolved mainly through two paradigms: 1) the deterministic sharpening filter and 2) Bayesian estimation. In this paper, we focus on a third paradigm: the conjunctive deblurring algorithm (CODA), which performs the deterministic filter and Bayesian estimation in a conjunctive manner. We next review these three paradigms by revealing the latent limitations.

A. First Paradigm: The Deterministic Filter

The deterministic filter can be modelled as deterministic function F of the input blurred image I: $F(I) = L$ with de- noting the output sharp image. The leftmost flowchart in Fig. 1 illustrates the first paradigm. One of the most well-known approaches in this paradigm is unsharp masking, of which the basic idea is to reduce the low frequency first, and then highlight the high-frequency components. The performance varies according to the adopted high-pass filters and the adaptive edge weights [13]–[15]. This approach assumes that the blurred edges do not drift too far away from the latent sharp edges; thus, it can handle only the defocus blurs and very small motion blurs. For very large blurs, the image narrow edges or details are severely damaged and very difficult to restore. A practical solution is to detect and restore large step edges explicitly or implicitly, which we call the step-edge-based filter (SEBF). Explicit SEBF first locates the step edge and then propagates the local intensity extreme toward the edge [6]. Implicit SEBF performs edge detection and restoration in a single step, based on zero crossings of high-pass filters. Commonly used implicit SEBFs include the shock filter [16], the backward diffusion [17], the morphological filtering [18], the fuzzy operator [19], and many other adapted versions. Compared with the second paradigm, i.e., Bayesian estimation, the SEBF has the following advantages: 1) The SEBF can handle various blurs without adaptation because it is independent of the blurring processes (blur models), and 2) the performance of the SEBF is not constrained by the sample number (SN) because it depends on image local features rather than sufficient samples.

II. REVIEW OF RELATED APPROACHES

. The aim of this paper is to retrieve the \ideal" image of an object, of which real cameras give only a degraded version, using a sequence of images. The previous section describes our model of the image formation process, including both optical blur and motion blur. This section presents related approaches in the literature. To our knowledge, the removal of the binedects of optical and motion blur has never been done before. However, these effects have been studied separately.

III. MOTION DEBLURRING AND PER-RESOLUTION FROM AN IMAGE SEQUENCE

In this section, we describe our work in detail. This extends the work of [8] who showed for the case of optical blur that, though restoring degraded images is an ill-conditioned problem, the use of a sequence of images to accumulate information about the object can help to partly overcome this indeterminacy. Here we also consider distortions introduced known to be a particularly ill-conditioned blur and have previously been studied for purely translational motion s and s ingle images only by motion blur. Motion blur and clarity blurred images are we have to be taken as a input and have to be produce output moreover the image sequences would be done in terms of pixel arrangements.

B. Second Paradigm: Bayesian Estimation

In this paradigm, both the kernel and image are taken as samples from some probability spaces. The goal is to solve for the unknowns that minimize the expected value of a loss function. The most commonly used loss function is the Dirac delta function, which yields the maximum a posterior (MAP) estimator. The center flowchart in Fig. 1 shows such a second-paradigm approach. Bayesian estimation has been recently hotly discussed because it has led to great progress. The success of it stems from the use of various image priors and estimators. In the smart work of [23], Levin *et al.* categorize the estimators into a MAP(L,K) case, which solves for both the kernel and image simultaneously, and a MAP (K) case, which solves for the kernel alone. It has been pointed out that naive a MAP (L,K) estimator fails to yield the desired result since the sparse priors prefer no-blur explanations [23]. Current MAP (L,K) estimators avoid the trivial solution by integrating many additional components, such as sharp edge detection [8], [10], [11], iterative likelihood update [10], and sparse repre- sentation under framelet and curvelet system [5]. By contrast, the MAP (K) estimator is well constrained and can accurately recover the true kernel if the image size is much larger than the kernel size [4]. Compared with the first paradigm, Bayesian estimation has the following advantages: 1) The approach is not sensitive to local narrow edges because it depends on statistics, object tracking approach: first the object is tracked through the sequence of images using an approach combining area-based and contour-based deformable models [1]. the tracking approach can be described as follows: (i) first the region is tracked by a deformable region based on texture correlation and constrained by the use of an a ne motion model. the use of texture correlation ensures the robustness of tracking for extured images, and is also more reliable than deformable contours for blurred images (ii) then the region contour is rened by a deformable contour. thus the detection of the region edges is more precise. it also helps to correct tracking errors made by the deformable region in the case of occlusions and specularities. this renement of the region contour is very useful if the image texture is poor.

and 2) it is not sensitive to image noise if the noise is not too much to change the statistics.

Although it is intuitively correct that Bayesian estimation can handle most blurred images, experiments of the aforementioned MAP estimators have shown that the performance is not always stable, sometimes even worse than the deterministic filters. The unstable performance gain is due to the following reasons: 1) A Bayesian estimator is built for a specific blur model and cannot handle other types of blurs without adaptation, and 2) the performance highly depends on the SNs and statistics.

The first limitation can be overcome by adopting different blur models. For example, by using the same variational Bayes method, Fergus *et al.* [4] address uniform blurs with a simple convolution model, whereas Whyte *et al*. [12] address non uniform blurs with a weighted integral model. The second limitation is very challenging to overcome because it is the latent limitation of Bayesian estimation [24]. We will show that, counter intuitively, the naive MAP (L,K)estimator and the MAP(K)estimator have similar performance in blind deconvolution and own the same limitation when dealing with very large blurs: In- sufficient samples make the global optimum no longer favour the true solution.

C. Third Paradigm: The Conjunctive Deblurring Algorithm

In this paradigm, the deterministic filter and Bayesian estima- tion are performed in a conjunctive manner. The rightmost flow- chart in Fig. 1 illustrates the CODA. The works in [11] and [25] can be viewed as two approximations of this paradigm, although the authors might not have motivated themselves in this way. In the work of Cho and Lee, a edge prediction scheme, which is a combination of the bilateral filter and the shock filter to- gether with a simple threshold method, is introduced to remedy the MAP (L,K) estimator. Xu and Jiaya enhance the work of Cho and Lee by proposing a gradient selection algorithm in order to exclude the narrow edges, which cannot be restored by the shock filter. The resultant methods can handle challenging examples beyond the capability of the first and second paradigms. Unfor- tunately, the latent reason why this paradigm can handle quite large blurs beyond Bayesian estimation is not given in either the work of Cho and Lee or that of Xu and Jiaya.

IV. **ALPHA TONAL CORRECTION**

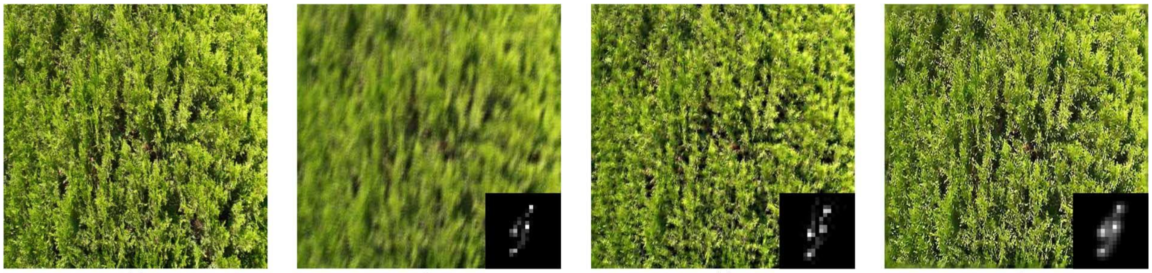
The adaptive tonal correction algorithm presented here uses the low- exposure or darker looking image as its input and enhances its appearance via tonal correction by making use of the mean (brightness) and variance (contrast) of the original blurred image in an adaptive manner. The main contribution here thus consists of an automatic process by which the tonal correction is done. The following tonal curve equation is considered in our algorithm is:

$$f(X) = \frac{\quad}{\log x} \qquad (2)$$

Whereas a parameter altering the contrast level. The optimum value of **is** taken to be the one that makes the contrast of the enhanced image equal to the contrast of the blurred image. To obtain the optimum parameter values in a computationally ef**fi**cient manner, the binary search approach is used.

Whereas x denotes pixel values of the input image, and the is a parameter altering the brightness s level. the optimal value of is considered to be the one that makes the brightness of the enhanced image equal to the brightness of the blurred image this correction also improves the image contrast. to further improve the contrast, a second tonal correction curve can be used to match the contrast of the blurred image among various possible curve functions.

$$g(x) = \frac{\quad}{2\tan(\beta/2)} \quad -(3)$$



(a) (b) (c) (d)

Fig. 23. (a) Clear image of which the textures are dominated by narrow edges. (b) Blurred image for testing. (c) Our deblurred result with PSNR (d) the result by Fergus *et al.* [4] for kernel estimation and the method [30] for nonblind deconvolution, with PSNR .

First select a rectangle region for kernel estimation and then use the kernel to segment the regions it affects with the algorithm in [30]. The segmentation result can be found in the supplementary material. We only deconvolve the regions identified as blurs. Amit *et al*. [40] use multiple images of different exposure time to recover the sharp image. Their result is shown by the top image in Fig. 21(c). Our algorithm produces a result with a similar level of sharpness.

Spatially Varying Blur Due to 6-D Camera Shake: Fig. 22(a) shows a spatially varying blurred image [41] due to a 6-D camera shake. Neel *et al.* [41] adopt six DOF inertial sensors to measure the camera motion during the exposure and then compute the blur kernel and deblurred image with an aided blind deconvolution [41]. Their result is shown in Fig. 22(b). We implement our algorithm on this example without adaptation. The obtained result is comparable to the result by the hardware approach of Joshi *et al.* The success is principally due to the integration of our deterministic filter, which is independent of the blur models. We notice that our result contains visible artifacts. Adaptation our method to spatially varying blur models [12], [42] has a high potential to improve the result, which is a trivial task since we do not constrain our method to a specific blur model.

V. DISCUSSION: THE LIMITATIONS OF OUR CODA

We have pointed out that the deterministic filters cannot recover the narrow edges totally damaged by the blur. Bayesian estimation with the strong ness-aware prior is capable of recovering the narrow edges only if a reasonably accurate kernel is available. In our CODA, the temporal kernel is computed by using the large step edges restored by the deterministic filter. Therefore, if the image structures are dominated by narrow edges, our CODA cannot produce an accurate blur kernel. Fig. 23 gives such an example for which the result of Bayesian estimation is better than ours. This problem is also faced by other CODAs. Texture hallucination techniques [26] might be adopted to restore the narrow edges. Our algorithm does not consider a number of common photographic effects, such as saturated pixels from strong lights, underexposed regions in very dark environments, and nonlinear tone scale. Incorporating these factors into our model will be an interesting future work.

VI. CONCLUSION

Rrecovery of the sharp image from a blurred one is an important and long- standing problem for many applications. In this paper, we have rest analyzed the potentials and limitations latent in recent methods when handling quite large blurs and significant noise. While our method. Out performs state-of-the-art methods both in robustness to noise and the capability of handling quite large blurs, it is still limited by the images dominated by narrow edges. Recovering the totally damaged narrow edges is still a very challenging problem faced by state-of- the-art methods and should attract further research efforts.

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